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2007 International Nuclear Atlantic Conference - INAC 2007
Santos, SP, Brazil, September 30 to October 5, 2007
ASSOCIAÇÃO BRASILEIRA DE ENERGIA NUCLEAR - ABEN
ISBN: 978-85-99141-02-1

COST-BASED OPTIMIZATION OF A NUCLEAR REACTOR CORE DESIGN: A PRELIMINARY MODEL

Wagner F. Sacco[1], Hermes Alves Filho[1] and Cláudio M. N.A. Pereira[2]

[1] Departamento de Modelagem Computacional - Instituto Politécnico
Universidade do Estado do Rio de Janeiro
Rua Alberto Rangel, s/n
28630-050 Nova Friburgo, RJ
{wfsacco, halves}@iprj.uerj.br

[2] Divisão de Reatores - Instituto de Engenharia Nuclear (IEN / CNEN - RJ)
Caixa Postal 68550
21945-970 Rio de Janeiro, RJ
cmnap@ien.gov.br

ABSTRACT

A new formulation of a nuclear core design optimization problem is introduced in this article. Originally, the optimization problem consisted in adjusting several reactor cell parameters, such as dimensions, enrichment and materials, in order to minimize the radial power peaking factor in a three-enrichment zone reactor, considering restrictions on the average thermal flux, criticality and sub-moderation. Here, we address the same problem using the minimization of the fuel and cladding materials costs as the objective function, and the radial power peaking factor as an operational constraint. This cost-based optimization problem is attacked by two metaheuristics, the standard genetic algorithm (SGA), and a recently introduced Metropolis algorithm called the Particle Collision Algorithm (PCA). The two algorithms are submitted to the same computational effort and their results are compared. As the formulation presented is preliminary, more elaborate models are also discussed.

1. INTRODUCTION

This paper presents a new formulation of a nuclear core design optimization problem that was originally introduced by Pereira *et al.* [1], and has been also solved by other authors (see [2], [3], and [4], for example). Consider a cylindrical 3-enrichment-zone PWR, with typical cell composed by moderator (light water), cladding and fuel. Briefly stated, the original problem consists in adjusting several reactor cell parameters, such as dimensions, enrichment and materials, in order to minimize the average peak-factor in this reactor, considering restrictions on the average thermal flux, criticality and sub-moderation.

Instead of obtaining a design that minimizes power-peaking factor, our aim is to minimize the fuel and cladding material costs, using this factor just as an operational constraint. This cost-based optimization problem is attacked by two metaheuristics, the standard genetic algorithm (SGA, [5]), and a recently introduced Metropolis algorithm called the Particle Collision Algorithm (PCA, [6], [4]).

The remainder of the paper is organized as follows. In the next section, the Particle Collision Algorithm is outlined. In section 3, the new formulation of the reactor design optimization problem is introduced. In section 4, the implementation of the algorithms is briefly described and the results are shown. Finally, in section 5, the concluding remarks are made.

2. THE PARTICLE COLLISION ALGORITHM

The PCA resembles in its structure that of simulated annealing [7]: first an initial configuration is chosen; then there is a modification of the old configuration into a new one. The qualities of the two configurations are compared. A decision then is made on whether the new configuration is "acceptable". If it is, it serves as the old configuration for the next step. If it is not acceptable, the algorithm proceeds with a new change of the old configuration. PCA can also be considered a Metropolis algorithm [8], as a trial solution can be accepted with a certain probability. This acceptance may avoid the convergence to local optima.

The pseudo code description of the PCA is shown in Figure 1 on its default version for maximization problems.

```
Generate an initial solution Old_Config
For n = 0 to # of iterations
        Generate a stochastic perturbation of the solution
                If Fitness(New_Config) > Fitness(Old_Config)
                        Old_Config := New_Config
                        Exploration ( )
                Else
                        Scattering ( )
                End If
End For

Exploration ( )
For n = 0 to # of iterations
        Generate a small stochastic perturbation of the solution
        If Fitness(New_Config) > Fitness(Old_Config)
                Old_Config := New_Config
        End If
End For
return

Scattering ( )
```

$$p_{scattering} = 1 - \frac{Fitness(New\_Config)}{Best\ Fitness}$$

```
If p_scattering > random (0, 1)
        Old_Config := random solution
Else
        Exploration ( );
End if
return
```

Figure 1. PCA's pseudo code.

The "stochastic perturbation" mentioned in the beginning of the loop consists in random variations in each variable's values within their ranges.

If the quality or fitness of the new configuration is better than the fitness of the old configuration, then the "particle" is "absorbed", there is an exploration of the boundaries searching for an even better solution. Function "Exploration ( )" performs this local search, generating a small stochastic perturbation of the solution inside a loop. In PCA's current version, it is a one-hundred-iteration loop. The "small stochastic perturbation" is similar to the previous stochastic perturbation, but each variable's new value is kept within the boundaries of the original value.

Otherwise, if the quality of the new configuration is worse than the old configuration's, the "particle" is "scattered". The scattering probability ($p_{scattering}$) is inversely proportional to its quality. A low-fitness particle will have a greater scattering probability. In a process similar to Monte Carlo's "Russian Roulette" [9], the configuration is "scattered" (replaced by a random configuration) or, following Metropolis, survives, with its boundaries explored ("else" branch of the function).

3. PROBLEM DESCRIPTION

After a brief description of the original problem in section 1, let's describe our new formulation.

The design parameters that may be changed in the optimization process are the same as in the original problem, and are shown in Table 1 with their variation ranges.

Table 1. Parameters range

Parameter	Symbol	Range
Fuel Radius (cm)	R_f	0.508 to 1.270
Cladding Thickness (cm)	Δc	0.025 to 0.254
Moderator Thickness (cm)	R_e	0.025 to 0.762
Enrichment of Zone 1 (%)	E_1	2.0 to 5.0
Enrichment of Zone 2 (%)	E_2	2.0 to 5.0
Enrichment of Zone 3 (%)	E_3	2.0 to 5.0
Fuel Material	M_f	{U-Metal or UO_2}
Cladding Material	M_c	{Zircaloy-2, Aluminum or Stainless-304}

In our formulation, the objective of the optimization problem is to minimize the fuel and cladding material costs of the proposed reactor, using the average peak-factor as an operational constraint, and, as in [1], considering that the reactor must be critical (k_{eff} = 1.0 ± 1%) and sub-moderated, providing a given average flux ϕ_0.

Our fitness function is given by the material costs of a single reactor cell:

$$\text{Fitness} = \pi h[\rho_f \$_f R_f^2 + \rho_c \$_c(2R_f\Delta c + \Delta c^2)] \quad , \qquad . \tag{1}$$

where: h = cell height (cm), which is fixed and equal to 163 cm [1];

ρ_f, ρ_c = fuel and cladding material densities (g/cm^3);

$\$_f$, $\$_c$ = fuel and cladding material prices (US$/g);

R_f = fuel radius (cm);

Δc = cladding thickness (cm).

Table 2, below, shows the prices and densities for each material.

Table 2. Prices and densities for fuel and cladding materials.

	Material	Price (US$/g)	Density (g/ cm^3)
Fuel	U-metal	0.099	19.10
	UO_2	0.187	10.96
Cladding	Zircaloy-2	3.040	6.84
	Aluminum	0.003	2.70
	Stainless-304	0.001	8.00

4. IMPLEMENTATION AND RESULTS

4.1. Implementation

In our tests, the GA setup was the same as in [3], including random seeds. Both algorithms were set up for 10,000 iterations, so that the results were obtained with the same computational effort.

Following Pereira's implementation of the original problem [1], the optimization algorithm sends to HAMMER Reactor Physics code [10] a solution and receives back power-peaking, average thermal flux and the effective multiplication factor. This information is translated to the algorithm by means of a preliminary fitness function that, if all constraints are satisfied, has the value of the average peak factor. Otherwise, it is penalized proportionally to the discrepancy on the constraint. Solutions with this preliminary fitness value above 1.75 or with power-peaking above 1.375 (upper bound of the results obtained by the canonical GA in [3]), receive a fitness value of 1,000,000. Otherwise, they receive a value as described by Eq. (1).

4.2. Results

Table 3 shows the results obtained by the SGA and by the PCA in five independent executions. Note that the genetic algorithm failed to obtain the best result in one of these executions.

Table 3. Results for the SGA and the PCA in 10,000 iterations

Experiment	SGA	PCA
#1	38.83	38.83
#2	38.83	38.83
#3	38.92	38.83
#4	38.83	38.83
#5	38.83	38.83
Average	38.85	38.83
Std. Dev.	0.045	0.000

Table 4 shows the best configurations obtained by both algorithms. These configurations achieved the same fitness value, suggesting that the search space may be multimodal.

Table 4. Configurations obtained by the SGA and the PCA.

		SGA	PCA
Objective	Fitness	38.83	38.83
Parameters	R_f (cm)	0.5080	0.5080
	Δr (cm)	0.0254	0.0254
	Δm (cm)	0.6924	0.5781
	E_1 (%)	2.472	2.557
	E_2 (%)	2.803	3.166
	E_3 (%)	4.409	5.000
	M_f	U-metal	U-metal
	M_c	Aluminum	Aluminum

5. CONCLUSIONS

We presented in this article a cost-based formulation of a nuclear reactor core design optimization problem and applied two metaheuristics to solve it. This problem is complex and multimodal, being quite challenging for stochastic optimization methods.

This new formulation is still in its early stages. Currently, we are looking for more realistic material prices. We are also planning to test other fitness functions as, for example, a composed objective function encompassing power-peaking, operational constraints, and costs.

ACKNOWLEDGEMENTS

Wagner F. Sacco is supported by FAPERJ (Fundação Carlos Chagas Filho de Amparo à Pesquisa do Estado do Rio de Janeiro) under postdoctoral grant E-26/152.661/2005 (Fixação de Pesquisador, Nível 3).

Cláudio M.N.A. Pereira gratefully acknowledges his research grant from CNPq (Conselho Nacional de Desenvolvimento Científico e Tecnológico).

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